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Self-Calibration of Cone-Beam CT Geometry Using 3D-2D Image Registration: Development and Application to Task-Based Imaging with a Robotic C-Arm

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Abstract

Purpose—Robotic C-arm systems are capable of general noncircular orbits whose trajectories can be driven by the particular imaging task. However obtaining accurate calibrations for reconstruction in such geometries can be a challenging problem. This work proposes a method to perform a unique geometric calibration of an arbitrary C-arm orbit by registering 2D projections to a previously acquired 3D image to determine the transformation parameters representing the system geometry.

Methods—Experiments involved a cone-beam CT (CBCT) bench system, a robotic C-arm, and three phantoms. A robust 3D-2D registration process was used to compute the 9 degree of freedom (DOF) transformation between each projection and an existing 3D image by maximizing normalized gradient information with a digitally reconstructed radiograph (DRR) of the 3D volume. The quality of the resulting “self-calibration” was evaluated in terms of the agreement with an established calibration method using a BB phantom as well as image quality in the resulting CBCT reconstruction.

Results—The self-calibration yielded CBCT images without significant difference in spatial resolution from the standard (“true”) calibration methods (p-value >0.05 for all three phantoms), and the differences between CBCT images reconstructed using the “self” and “true” calibration methods were on the order of 10^{-3} mm^{-1} . Maximum error in magnification was 3.2%, and back-projection ray placement was within 0.5 mm.

Conclusion—The proposed geometric “self” calibration provides a means for 3D imaging on general non-circular orbits in CBCT systems for which a geometric calibration is either not available or not reproducible. The method forms the basis of advanced “task-based” 3D imaging methods now in development for robotic C-arms.

Keywords

task-based imaging; cone-beam CT; imaging task; image-guided interventions

I. INTRODUCTION

Intraoperative CBCT systems require accurate specification of system geometry to perform image reconstruction. With the advent of task-based imaging and the availability of robotic C-arm CBCT systems such as the Artis Zeego (Siemens Healthcare, Figure 1), the system geometry can be customized to the patient and imaging task [1]. Current calibration techniques are typically performed using a specialized phantom and assume that the system maintains the same geometry with every acquisition. Such methods are ill suited to noncircular geometries that may vary between imaging studies. Additionally, there are factors that introduce errors to the geometric calibration, such as C-arm flexion under gravity [2] and system jitter [3], causing a previous geometric calibration of the system to no longer represent the true geometry and cause artifacts in the reconstructed image [4]. We propose a method that provides an accurate, “self-calibration” of geometry with each scan.

In CBCT for image-guided interventions, a previously acquired 3D image of the patient (i.e. a pre-operative CT image) is readily available and can be utilized to calculate the transformation of the projection image via 3D-2D image registration, which corresponds to the system geometry. This process enables the mapping of anatomical homologous locations in each projection image and the previously acquired 3D image, which is equivalent to considering the patient herself as a fiducial during calibration. This “self”-calibration method takes advantage of rigid, high-contrast anatomy to simultaneously determine all necessary parameters to describe the geometry of the system and produce a set of projection matrices ($\mathcal{P}$) which can subsequently be used to perform image reconstruction.

II. METHODS

System Geometry

The system geometry for a single projection is represented in Figure 2 where the world coordinate frame is defined as the detector coordinate frame. The vector $(t_x, t_y, t_z, \theta_x, \theta_y, \theta_z)$ defines the object position and orientation and the vector (s_x, s_y, s_z) defines the source position. Together these 9 degrees of freedom (DOF) uniquely define $\mathcal{P}$ which relates a 3D point to its projection in the 2D detector plane by;

$$\begin{pmatrix} u \\ v \\ 1 \end{pmatrix} \sim P \begin{pmatrix} x \\ y \\ z \end{pmatrix} = \begin{pmatrix} s_z & 0 & s_x & 0 \\ 0 & s_z & s_y & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} R_{3 \times 3}(\theta_x, \theta_y, \theta_z) & t_x - s_x \\ & t_y - s_y \\ & t_z - s_z \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ z \\ 1 \end{pmatrix} \quad (1)$$

3D-2D Registration

The algorithm for 3D-2D registration iteratively solves for the transformation of a 3D image (i.e. the pre-operative image) that maximizes similarity between an acquired 2D projection and DRRs of the 3D volume. This registration yields the 9 DOF needed to create $\mathcal{P}$ and produces a scan-specific geometric calibration of the imaging system. This algorithm was previously described in detail in [6] and is summarized in Figure 3.

Similarity metric—Normalized gradient information (NGI) was used as a similarity metric, described in [6]. This metric assesses the gradient magnitude at each pixel location and ignores strong gradients appearing in only one of the projection images, which provides robustness to inconsistencies between the projection image and the DRR. The NGI is the gradient information of the moving and fixed images, normalized to that of the moving image itself:

$$NGI(I_1, I_0) = \frac{GI(I_1, I_0)}{GI(I_0, I_0)} \quad (2)$$

where GI is the gradient information defined as:

$$GI(p_1, p_2) = \sum_{i,j \in \Omega} m(i, j) w(i, j) \min(|\nabla p_1(i, j)|, |\nabla p_2(i, j)|). \quad (3)$$

The min operator is used to ignore mismatching gradients by weighting only those gradients that are present in both images. Mismatching gradients can occur due to surgical tools in the field of view, deformations, or image artefacts. ∇p is a gradient vector where the gradient notation indicates the change in pixel value along the i and j directions at pixel location (i, j) within the image:

$$\nabla p(i, j) \triangleq \left(\frac{d}{di} p(i, j), \frac{d}{dj} p(i, j) \right). \quad (4)$$

The weighting term w was defined as:

$$w(i, j) = \frac{a_{i,j} + 1}{2} \quad (5)$$

$$a_{i,j} = \frac{\nabla p_1(i, j) \cdot \nabla p_2(i, j)}{|\nabla p_1(i, j)| |\nabla p_2(i, j)|} \quad (6)$$

where $a_{i,j}$ represents the cosine between gradient vectors at location (i, j) . Alternative similarity measures include gradient correlation (GC), but NGI was found to be the most robust against mismatch and noise in the application of 3D-2D registration of images with comparable intensity scales [8].

Initialization—Additional perturbations that would describe changes in system geometry of a realistic C-arm system (i.e. gravitational flex, system jitter, etc.) were added to a previously obtained geometric calibration and this perturbed geometry was used to provide an initialization for the self-calibration. Systematic perturbations were introduced by adding a constant value (δ) to the measured 9 DOF and random perturbations were introduced by adding a Gaussian distributed random variable with zero-mean and variance (σ). The perturbations were $\delta = \sigma = 10$ mm for s_x, s_y, t_x, t_y , $\delta = \sigma = 4$ mm for s_z, t_z , and $\delta = \sigma = 4^\circ$ for $\theta_x, \theta_y, \theta_z$ [4]. The 2D projections images were each downsampled by a factor of 3 and the 3D volume was downsampled by a factor of 2. This downsampling of the images helped to

smooth noise and small gradients in the images that may negatively affect the registration while maintaining enough detail to register the images to the desired accuracy.

Optimization—The covariance matrix adaptation-evolutionary strategy (CMA-ES) described in [7] was chosen to solve the optimization problem:

$$\hat{s}, \hat{t}, \hat{\theta} = \underset{s, t, \theta \in S}{\operatorname{argmax}} NGI(I_1, I_0(s, t, \theta)), \quad (7)$$

where S represents the search range.

CMA-ES generates populations of sample points with each iteration and adjusts the mean and covariance matrix of the sample points according to the optimization problem to create a new generation. This repeats until convergence. Population size (λ) is therefore an adjustable parameter within the optimization framework. Choosing λ is a tradeoff in computation speed and robustness against false optima [8]. For this work, the population size was chosen to be 100 for all projections to emphasize accuracy of the registration.

The stopping criterion for the CMA-ES algorithm was defined in terms of diminishing change in each of the 9 DOF parameters describing the pose of the object in CT coordinate space. For this application, a high level of accuracy was needed to determine the pose of the object to less than half the pixel size. With a typical detector pixel pitch on the order of 0.2 mm, the algorithm was run for a number of iterations required to find the object pose to within 0.1 mm. To be well within the desired accuracy tolerance for this preliminary work, the stopping criterion was chosen to be 0.01 mm for change in translations, and 0.01 degrees for rotations.

Experimental Setup

Three phantoms were used in this study: a cylinder phantom with a thin tungsten wire and several acrylic spheres; a clutter phantom in which acrylic and Teflon spheres were suspended in gelatin along with a tungsten wire; and an anthropomorphic head phantom also containing a tungsten wire insert. Each phantom was imaged twice in sequence, with each phantom shifted by several centimeters and tilted several degrees for the second acquisition to simulate (rigid) change in patient position from pre-op to intra-op setup. A CBCT bench was used, with each acquisition involving 360 projections obtained over 360° [1536×1536 pixels] at 100 kVp, 63 mAs. All images were reconstructed using 3D filtered backprojection with isotropic (0.5 × 0.5 × 0.5) mm³ voxels.

Projections from the first acquisition were reconstructed using a standard geometric calibration procedure [5]. Projections from the second acquisition were then registered to this 3D volume using the 3D-2D registration algorithm described above to obtain one $\mathcal{P}$ per projection. A modified FDK algorithm was used for image reconstruction of the second set of images where the backprojection geometry for each projection was defined using $\mathcal{P}$.

Analysis of Geometry Estimates

To compare the results of the self-calibration to the reference calibration, image quality was examined between reconstructions through FWHM measurements of the point-spread function (PSF) created by the tungsten wire inserts for 10 axial slices. In addition, displacement of the perpendicular ray that connects the source to the piercing point was measured and compared by calculating the shortest distance from the ray to the point (0,0,0) within the object coordinate frame. The view-by-view magnification of the system was also compared between the “true” calibration and self-calibration methods.

III. RESULTS AND BREAKTHROUGH WORK

The perpendicular ray placement associated with the two calibration methods corresponded closely for all projections (as shown in Figure 5a). All of the displacements were less than 1 mm (at the detector), indicating that the self-calibration is placing the rays with sufficient precision to fall within the same 0.5 mm isotropic voxel of the reconstructed 3D image through backprojection. Figure 5b shows the reference and calculated magnifications of the system for all projections. The sinusoidal nature of the magnification is due to slightly off-center positioning of the phantoms and differs by at most 3.2% between self-calibrated geometry and reference geometry.

None of the phantoms exhibited a significant difference in FWHM between the two calibration methods ($p = 0.06$ for the cylinder phantom, $p = 0.75$ for the clutter phantom, and $p = 0.46$ for the head phantom) as shown in Figure 6, indicating that the self-calibration method accurately corrected the perturbations imparted to the system geometry and yielded an image comparable to a standard calibration.

Visual inspection of the reconstructed 3D images in Figure 7 shows that structures of interest are accurately reconstructed using the self-calibration at a level of image quality comparable to (and perhaps superior to) the reference calibration. Additionally, the residuals between the two images are on the order of 10^{-3} mm^{-1} further showing that self-calibration computed an accurate representation of the system geometry despite poor initialization.

IV. DISCUSSION AND CONCLUSIONS

This work shows the feasibility of using a “self” calibration directly from the acquired projection data in CBCT. The method is applicable to systems involving noncircular orbits and facilitates the realization of task-based imaging on sophisticated C-arm platforms. Future work includes additional testing on the Zeego C-arm system, as well as modifying the registration algorithm for robust initialization. For example, in the case of a system with adjustable geometry, initialization of the first projection could be provided by basic input and each subsequent projection could be initialized using the estimated geometry of the previous projection in a bootstrapping manner. The system is also generally applicable as a refinement to systems that are believed to be well calibrated but may suffer slight irreproducibility. Similarly, the method allows reliable CBCT reconstruction in situations where the geometric calibration is no longer valid (e.g., out of date) and provides a potential sentinel to detect when geometric calibration has fallen out of tolerance.

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Figure 1.
Robotic C-arm with adjustable geometry and a variable orbit [5].

Figure 2.
Projection geometry and parameters associated with source, CT, and detector coordinates.

Figure 3.
Illustration of the 3D-2D registration algorithm.

(a) **(b)** **Figure 4.**

(a) Experimental bench for CBCT imaging. (b) Phantoms used for experimentation, (left to right) simple cylinder, spherical clutter in gelatin, and an anthropomorphic head.

Figure 5.

(a) Difference in perpendicular ray placement between true geometry and geometry found using 3D-2D registration. (b) Magnification of the system for each projection.

Figure 6.

Boxplots of FWHM measurements of the wire PSF in each phantom. P values for the cylinder, clutter, and head phantom data sets are 0.06, 0.75, 0.46 respectively. Images of the PSF are shown with length bar marking 1 mm length in far right image.

Figure 7.

3D image reconstructions. For each phantom (a – c); reconstructed image using self-calibration shown in the first column, zoom on reconstructed image using self-calibration shown in second column, zoom of same area from reconstruction using reference calibration shown in third column, difference between zoomed areas shown in fourth column.